Nonlinear model predictive engine airpath control with dual-loop exhaust gas recirculation and variable nozzle turbocharger

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A Nonlinear MPC as the Real-Time Controller of the Airpath of Engines with Dual-Loop EGR and VNT

Zihao Liu, Arash M. Dizqah, Jose M. Herreros, Joschka Schaub and Olivier Haas

Abstract—The control of engine airpath is a multi-objective tracking problem that aims to achieve a trade-off between emissions and fuel economy. Multiple control variables are simultaneously adjusted to accommodate both fast, slow and coupled nonlinear dynamics. This work proposes a Nonlinear Model Predictive Controller (NMPC) exploiting a convex and multi-rate prediction model to control in real-time the airpath of a compression ignition engine equipped with dual-loop Exhaust Gas Recirculation (EGR) and Variable Nozzle Turbocharger (VNT). Simulation studies and Hardware-in-the-Loop (HiL) implementation of the controller on a 480MHz ARM Cortex-A7 processor demonstrate reduced tracking error for intake manifold pressure and oxygen concentration by 12% and 21% respectively, whilst showing a 1% improvement in fuel economy. The control algorithm runs in real-time with both average and maximum computational time on HiL, being respectively 1.80 ms and 2.94 ms, below the required control interval of 10 ms.

Index Terms—Hardware-in-the-loop, Nonlinear Model Predictive Control, Dual-loop Exhaust Gas Recirculation, Variable Nozzle Turbocharger

I. INTRODUCTION

Regulations of vehicles including passenger cars (conventional and hybrids), trucks, trains and marine vessels restrain engines tailpipe emissions and fuel consumption [1]. VNT and dual-loop EGR enable modern engines to achieve reduced emissions. VNT builds up the intake manifold pressure by recovering part of the otherwise waste energy from the exhaust gas. VNT allows comparable torque and power with smaller-size and hence more efficient engines [2]. EGR lowers in-cylinder oxygen concentration and local peak combustion temperature by diluting the combustion charge to reduce the generation of NOx emissions [3]. However, EGR could increase soot emissions, known as the NOx-soot trade-off, as well as adversely affecting torque tracking during aggressive accelerations [4].

Dual-loop EGR systems combine a High Pressure (HP) and an additional Low Pressure (LP) EGR route. The HP EGR route connects the exhaust and intake manifold, whilst the LP EGR connects the downstream of the Exhaust Aftertreatment System (EATS) and the air intake. Compared to HP EGR, LP EGR delivers a more homogeneously mixed charge at a higher volumetric efficiency due to cooler recirculating gas. Using LP EGR also reduces the amount of HP EGR and hence lowers the pressure drop upstream of the turbocharger. However, LP EGR takes longer to respond and recirculates gases with more condensed water that could reduce the life-span of the compressor [5]. The optimal split between the HP and LP loops depends on the engine operating condition [6].

The joint use of EGR and VNT actuators affects the pressure at the intake manifold and the oxygen concentration inside the cylinders. This makes the associated control problem multi-variable. The controller must also consider different operating constraints, such as preventing VNT from choking and surging, whilst delivering sufficient mass of oxygen to meet the torque demand. The use of LP EGR adds an extra degree of freedom to this nonlinear and multi-variable control problem.

Different techniques have been adopted to solve the control problem of the engine airpath, including robust $H_{\infty}$ control in [7], Lyapunov function based inverse optimal control with feedback linearisation in [8] and PI/PID control in [9]. Alternatively, Model Predictive Control (MPC) is a method that systematically considers the dynamics and constraints of multi-variable systems to calculate the optimal control solution [10]. Using existing theoretical frameworks and numerical

ACRONYMS

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>BMEP</td>
<td>Brake Mean Effective Pressure</td>
</tr>
<tr>
<td>BSFC</td>
<td>Brake Specific Fuel Consumption</td>
</tr>
<tr>
<td>CAN</td>
<td>Controller Area Network</td>
</tr>
<tr>
<td>CI</td>
<td>Compression Ignition</td>
</tr>
<tr>
<td>EATS</td>
<td>Exhaust Aftertreatment System</td>
</tr>
<tr>
<td>ECU</td>
<td>Electronic Control Unit</td>
</tr>
<tr>
<td>EGR</td>
<td>Exhaust Gas Recirculation</td>
</tr>
<tr>
<td>HiL</td>
<td>Hardware-in-the-Loop</td>
</tr>
<tr>
<td>HP</td>
<td>High Pressure</td>
</tr>
<tr>
<td>LP</td>
<td>Low Pressure</td>
</tr>
<tr>
<td>LUT</td>
<td>Look-up Table</td>
</tr>
<tr>
<td>MPC</td>
<td>Model Predictive Control</td>
</tr>
<tr>
<td>NMPC</td>
<td>Nonlinear Model Predictive Controller</td>
</tr>
<tr>
<td>OCP</td>
<td>Optimal Control Problem</td>
</tr>
<tr>
<td>OFR</td>
<td>Oxygen Fuel Ratio</td>
</tr>
<tr>
<td>OS</td>
<td>Operating System</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root Mean Square Error</td>
</tr>
<tr>
<td>VNT</td>
<td>Variable Nozzle Turbocharger</td>
</tr>
<tr>
<td>WLTC</td>
<td>Worldwide harmonized Light vehicles Test Cycles</td>
</tr>
</tbody>
</table>
This work contributes to the knowledge by:comparable processor than an Electronic Control Unit (ECU).

Direct use of nonlinear models within the MPC formulation, on the other hand, does not need pre-analysis to identify the operating zones and captures the system dynamics with better resolution as compared to piece-wise linear models. However, it may introduce non-convexity to the control problem that significantly increases the computational cost without guarantee of convergence and solution quality. Physics-based models of engine are non-convex [8, 15] and difficult to fit well to actual engines [16]. Data-driven models, along with appropriate selection of numerical solvers for constraints handling, offer a promising alternative for real-time implementation [17]. To reduce computational burden, Liao-McPherson et al. [16] use data-driven models and a move-blocking technique that fixes the values of controls over some of the prediction samples and hence reduces the degrees of freedom. The experimental study of NMPC in [18] shows a worst case of 0.72 ms on a rapid prototyping unit with a processor of 2.6 GHz. Murilo et al. [19] use a parameterised NMPC where the optimal control is solved independently to the nonlinear system model and illustrates a range of computation time between 6.5 ms and 10 ms on a 480 MHz processor. A NMPC in [20] that modifies set points to maximise engine efficiency whilst constraining emissions reported a worst case execution time of 1.8 ms on a 800 MHz processor. Alternatively, the control law of NMPC can be approximated by a machine learning model that runs online to achieve sub-millisecond performance [21]. An artificial neural network is also reported to control the delivery of EGR for a spark ignition engine [22]. However, machine learning and neural network must be re-trained for each change of control design and tuning.

This work presents a control design for airpath with dual-loop EGR that addresses a more complex tracking problem than [18–21]. Meanwhile, the presented controller shows more promising computational results than [18–21] whilst using a comparable processor than an Electronic Control Unit (ECU). This work contributes to the knowledge by:

1) Proposing a novel NMPC strategy that uses a convex multi-rate prediction model of the airpath of a Compression Ignition (CI) engine. The controller employs process dependent prediction step length. A standard 0.01 s is used for the prediction of in-cylinder oxygen concentration, however a slower 0.1 s is used for that of boost pressure. The strategy shows better tracking performance and fuel economy than a EURO 6 production-line controller.

2) Demonstrating the real-time performance of the proposed NMPC on a HiL implementation using a comparable processor than an ECU.

II. SYSTEM DESCRIPTION & MODELLING

Fig.1 illustrates the target engine used for this work. It is a two litre EURO-6 CI engine equipped with VNT and dual-loop EGR. The available measurements of the engine to the controller include pressure and temperature of the intake manifold, engine speed and the coolant temperature. The experimentally validated model of the engine in [23, 24] and the corresponding production-line controller in [23, 25], provided by FEV GmbH, were adopted in this work.

The engine model, referred to as plant model hereafter, is physics-based with empirically determined parameters stored in Look-up Tables (LUTs). It has a time resolution of 0.01 s. The production-line controller runs at 0.01 s and includes the control of injection (common rail, timing & mass), EATS, and airpath. The airpath control of the production-line controller translates a target of engine-out NOx emission to set points of cylinder oxygen and boost pressure, which are then tracked by a combination of feed-forward and PI controllers.

This papers proposes a NMPC that utilises a prediction model of the airpath with the following states:

1) Dynamic states $\mathbf{x} = [p_2, x_O]^T$ where $p_2, x_O$ are boost pressure and cylinder oxygen concentration in kPa and mol/mol, respectively.

2) Intermediate states $p_{\text{loss}}, m_{\text{cyl}}$ which represent the pumping loss in kPa and the mass of cylinder charge in milligrams, respectively.

3) Controls $\mathbf{u} = [u_h, u_t, u_e]^T$ where $u_h, u_t, u_e$ are desired valve positions in percentage for HP, LP EGR and VNT, respectively. The corresponding actual valve positions are $\mathbf{\tilde{u}} = [\tilde{u}_h, \tilde{u}_t, \tilde{u}_e]^T$. 
4) Disturbances \( \rho = [n_{e, b}, \text{bmepe}, T_{\text{co}}, T_{2}]^T \) representing engine speed (rpm), Brake Mean Effective Pressure (BMEP) (bar) and the coolant and intake manifold temperature (K), respectively.

The dynamics of boost pressure and in-cylinder oxygen concentration have distinct time scales. Using step changes of VNT and HP EGR, it takes up to, respectively, 4 and 0.1 s for boost pressure and in-cylinder oxygen to settle. Compared to the control interval of 0.01 s, boost pressure presents much slower dynamics than the in-cylinder oxygen. Fig. 2 presents the auto-correlation of boost pressure and in-cylinder oxygen concentration. It reveals the correlation of the current value of the dynamic state with respect to its previous values, taking account of changes in both control and disturbances. The oxygen concentration has much shorter time lag than the boost pressure for each threshold of correlation. Based on the identified slow and fast dynamics, this work adopts a long and short prediction interval, which are 0.1 and 0.01 s for boost pressure and in-cylinder oxygen concentration, respectively.

The resulting prediction models are represented in generalised form \( f(\cdot) \):

\[
\dot{u}_{k+1} = t_s T u_{k+1} + (I - t_s T) \dot{u}_k \\
p_{2,k+10} = f(p_{2,k}, x_{O,k}) + f(\dot{u}_v, k; \rho) \\
x_{O,k+1} = f(p_{2,k}, x_{O,k}) + f(u, k; \rho) \\
p_{\text{loss}, k} = f(p_{2,k}, u_v, k; \rho) \\
m_{\text{cyl}, k} = f(p_{2,k}; \rho) \\
\lambda_{O,k} = \frac{(m_{\text{fuel}} + \frac{m_{cyl}}{\text{Ofr}})}{\text{Ofr}_{\text{stoich}}} \tag{6}
\]

where (1), (2) and (3) govern the dynamics of actuator valves, boost pressure and cylinder oxygen, respectively. Additionally, pumping loss and cylinder mass intake are modelled as (4) and (5), respectively. The sampling time is represented as \( t_s \) and is 10 ms. \( T \) is a diagonal matrix containing the time constants for the HP EGR, LP EGR and VNT. \( \lambda_O \) is the fraction of Oxygen Fuel Ratio (OFR) over its stoichiometric value \( \text{Ofr}_{\text{stoich}} \). \( M_{o2}, M_{\text{air}} \) represent the molar mass of oxygen and air, and have constant values of 32 g/mol and 28.97 g/mol, respectively.

The functions \( f(\cdot) \) are the multi-parametric polynomials introduced in [26]. The model is identified to be convex, which allows the solver to quickly find the global optimum. The convexity is guaranteed by enforcing the coefficients of the polynomials to be positive. Since the states and controls are non-negative by their physical meaning, the positive coefficients result in a Hessian matrix with non-negative elements. This allows the Hessian matrix to be positive semi-definite. The convex models are pruned iteratively and verified against the WLTC data set generated using the production-line controller. The identification process uses a bounded value least square algorithm and is described with more details in [26]. Table 1 summarises the accuracy of the resulting model over the WLTC.

### III. Controller Design

The primary objective of the developed NMPC strategy is to track the set points of boost pressure and in-cylinder oxygen concentration (denoted \( p_{2,sp} \) and \( x_{O,sp} \), respectively). The set points are calculated by the production-line controller using LUTs. Apart from tracking the set points, the NMPC has additional objectives as follows:

1) minimise control variation of all valves;
2) operate VNT as efficiently as possible by minimising \( (u_v - u_{v,eff})^2 \), where \( u_{v,eff} \) is the most efficient VNT valve position;
3) minimise pumping loss, thus improving mechanical efficiency and hence fuel economy.

The value of \( u_{v,eff} \) depends on the operating condition of the VNT and may be read from system specific LUT from manufacturer or derived from experiments.

The resulting Optimal Control Problem (OCP) is formulated as follows:

\[
\{u^*\} = \arg \min_{u \in \mathcal{U}} J(x, u, \rho) \tag{7a}
\]

subject to \( (1), (4), (5), (6) \) \tag{7b}

\[
p_{2,k+i} = p_{2,k}, i \in \{0, 1, \ldots, 9\} \tag{7c}
\]

\[
u_{v,k+i} = u_{v, k}, i \in \{1, \ldots, 9\} \tag{7d}
\]

\[
I_{p2,k+i} = I_{p2,k} - t_s (p_{2,k} - p_{2,sp}), i \in \{1, 2, \ldots, 10\} \tag{7e}
\]

\[
I_{o2,k+i} = I_{o2,k} - t_s (x_{O,k} - x_{O,sp}) \tag{7f}
\]

![Fig. 2. Auto-correlation of (a) boost pressure, (b) cylinder oxygen concentration before combustion, using the data over the WLTC with the production-line controller.](image-url)

<table>
<thead>
<tr>
<th>Model</th>
<th>RMSE</th>
<th>NRMSE</th>
<th>( R^2 _T )</th>
<th>Number of Polynomials</th>
</tr>
</thead>
<tbody>
<tr>
<td>( p_{2, [\text{kPa}]} )</td>
<td>10.76</td>
<td>0.56</td>
<td>83.17</td>
<td>13</td>
</tr>
<tr>
<td>( x_{O, [\text{mol/mol}]} )</td>
<td>0.01</td>
<td>0.53</td>
<td>75.84</td>
<td>19</td>
</tr>
<tr>
<td>( p_{\text{loss}, [\text{kPa}]} )</td>
<td>8.07</td>
<td>0.55</td>
<td>71.45</td>
<td>28</td>
</tr>
<tr>
<td>( m_{\text{cyl}, [\text{mg}]} )</td>
<td>10.03</td>
<td>0.92</td>
<td>99.65</td>
<td>4</td>
</tr>
</tbody>
</table>

*()\(^*\) indicates a model with 0.1 s prediction interval whilst the rest are of 0.01 s.
where $I_{p2}, I_{o2}$ are the tracking error integral of the boost pressure and oxygen concentration, respectively, to eliminate steady state tracking errors. The boost pressure is initialise from the sensor reading. Since the boost pressure is predicted every ten prediction steps, the intermediate values are held at zeroth order in (7c). The in-cylinder oxygen concentration is estimated with an existing estimator within the production-line controller based on LUTs. The disturbances $p$ are assumed to be constant throughout the prediction horizon. The control horizon is assumed equal to the prediction horizon $n_p$. The vector $\{u\}$ is made of decision variables $[u_{h1}, u_{h2}, ..., u_l, u_{l1}, u_{l2}, ..., u_{v1}, u_{v,eff10}, ...]^T$. $[u_{h0}, u_{l0}, u_{v0}]^T$ are the control applied at last control interval.

The constraint (7k), known as lambda limit, requires a sufficient mass of oxygen for the engine to deliver the required torque. However, hard enforcement of (7k) is not realistic due to faster torque increments than the dynamics of cylinder mass intake and oxygen concentration. Whilst the fuel injection controller cuts excessive fuel reactively, (7k) is considered as a soft constraint that allows minor violation during online solving via penalty functions [27]. Using (7k) improves the torque tracking of the controller. Meanwhile, (7k) is only required when $k = 1$ because further predictions are made unreliable since boost pressure and fuel mass are assumed constant over the next ten predictions.

The objective function $J$ and stage cost function $L$ are defined as follows:

$$J := \sum_{i=1}^{n_p} L_i$$

$$L_i := \zeta \times \{(N_{\hat{z}}, \hat{\xi})^T Q (N_{\hat{z}}, \hat{\xi}) + (N_{\hat{u}} u) R_{\hat{u}} (N_{\hat{u}}, \hat{u}) + (N_{\Delta u} \Delta u)^T R_{\Delta u} (N_{\Delta u}, \Delta u) + \alpha (n_{\text{loss}})^2\}$$

where $Q \succ 0; R_1 \succeq 0; R_2 \succ 0$

$N_{\hat{z}} \succeq 0; N_{\hat{u}} \succ 0; N_{\Delta u} \succ 0$

$\hat{\xi} = x_i - [p_{2,sp} X_{O,sp}] - [K_{l,p2} 0 0 K_{l,o2} 0] [I_{p2,i}]$

$u_i = u_i - [0 0 u_{v,eff}]$

$\Delta u_i = u_i - u_{i-1}$

$K_{l,p2}, K_{l,o2}$ are integral gains; $x_i, u_i$ are state and control vectors defined as $[p_{2,i}, X_{O,i}]$, $[u_{h,i}, u_{l,i}, u_{v,i}]$ respectively. Diagonal matrices $N_{\hat{z}}, N_{\hat{u}}, N_{\Delta u}$, and scalar $n_{\text{loss}}$ are positive normalisation factors to scale $\hat{\xi}, \hat{u}, \Delta u$ and $p_{\text{loss}}$ to unit value. $Q, R_1, R_2$ are diagonal weighting matrices, $\alpha$ is the weighting scalar for the pumping loss term.

Having formulated the control problem, the next section discusses the online implementation of the controller.

IV. ONLINE IMPLEMENTATION OF THE CONTROLLERS

The developed NMPC is evaluated by a simulation study and HiL implementation. The simulation study uses a desktop computer of Intel Xeon E5-1620 CPU (3.60 GHz), 12GB RAM and Win10 Operating System (OS). The HiL implementation uses a dSPACE® SCALEXIO system [28] and the A80Q7 evaluation board [29], as shown in Fig 4. The A80Q7 board is equipped with eight ARM® cores including four Cortex-A15 (1200 MHz) and four Cortex-A7 cores (480 MHz). However, only one of the A7 cores is used to evaluate the developed controller to make it comparable to ECUs.

A proprietary solver for the NMPC strategy is developed which uses exact-Newton method with the number of iterations fixed to six. Six iterations of exact-Newton method is chosen as it offers the best trade-off between performance and realtime computational requirements. The equality and inequality constraints are converted to barrier functions described in [26]. The solver routine is written in MATLAB® and uses the embedded coder® for the HiL implementation.

When implemented on HiL, the A80Q7 board executes the entire engine control software of the production-line controller including fuel injection, common rail, EATS, and airpath. The airpath control software is then replaced by the developed NMPC and tested subsequently. All signals are represented with 1 byte and transmitted on CAN bus at a rate of 1000 kbit/sec due to lack of analogue and digital IOs. There are 20 feedback signals and 8 control signals, carried by three receive (RX) and one transmit (TX) CAN packets. The host computer logs the states of the engine, whilst the A80Q7 board logs the computational time. The control software runs as a single thread on a Cortex-A7 core that is free from other tasks.

Both simulation and HiL use WLTC with warm engine start. WLTC comprises four duty parts, namely light (L), medium (M), heavy (H) and extra-heavy (EH). The prediction horizon of the developed NMPC is set to 10 steps. This requires one prediction of boost pressure and nine predictions of the in-cylinder oxygen due to a different prediction interval adopted for the two dynamics. The values of $u_{v,eff}, K_{l}(), N_{l}(), n_{\text{loss}}$.
Fig. 4. A photo of the dSPACE SCALEXIO system used for HiL implementation of the controllers. The A80Q7 board (highlighted by red dashed box) is connected to the SCALEXIO and external computer via CAN bus and Ethernet, respectively.

TABLE II
WEIGHTINGS AND PARAMETERS USED BY NMPC FOR THE ENTIRE WLTC.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Use</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Q )</td>
<td>Weighting Matrix</td>
<td>diag([0.500, 0.200])</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>Weighting</td>
<td>0.001</td>
</tr>
<tr>
<td>( R_1 )</td>
<td>Weighting Matrix</td>
<td>diag([0.006, 0.100, 0.050])</td>
</tr>
<tr>
<td>( R_2 )</td>
<td>Weighting Matrix</td>
<td>diag([0.010, 0.001, 0.050])</td>
</tr>
<tr>
<td>( n_p )</td>
<td>Prediction Horizon</td>
<td>10</td>
</tr>
<tr>
<td>( u_{v, eff} )</td>
<td>Most efficient VNT valve percentage</td>
<td>80</td>
</tr>
</tbody>
</table>

are set to constant values throughout the WLTC. Table II illustrates values of the weightings \( Q, R_1 \) and \( R_2 \) in (8), as well as some of the parameters of the OCP. The matrix element is noted in the form of \((\cdot)_{ij}\), where \( i, j \) stands for the row and column indices, respectively.

V. SIMULATION AND HIIL RESULTS

Performance of the proposed NMPC is compared against the production-line controller in terms of the tracking Root Mean Square Error (RMSE) of boost pressure and cylinder oxygen, torque tracking RMSE and mean Brake Specific Fuel Consumption (BSFC). The improvements of the performance criteria, using simulation study and HiL, are represented in percentage in Table III and IV, respectively. A zero-mean Gaussian noise is added to the feedback signals to examine the controller performance under realistic driving conditions. These feedback signals include engine speed, intake manifold temperature & pressure, coolant temperature and an estimation of the fuel mass injection. The Gaussian noise for each signal has a specified variance that is proportional to the range of the signal observed over the WLTC. Whilst an integrated pressure and temperature sensor can reach 0.5% accuracy [30], this proportion is chosen as 5% and 10% to consider worst case scenarios. All the provided plots use normalised values.

Table III compares performance of NMPC against the production-line controller for different duty parts of WLTC and for three levels of additive measurement noise. The proposed NMPC achieves better tracking of set points and
torque whilst offering better fuel economy when there is no additive noise. With a 5% Gaussian noise, the advantage of each objective degrades moderately. Even with a 10% noise, the NMPC still achieves better performance in all criteria against the production-line controller. This shows a consistent performance margin of the developed controller under measurement noise.

The tracking performance of the two controllers differ mainly during transients. Fig. 5 shows that the NMPC gains advantage during transients. The NMPC demonstrates the least improvement in the EH duty part which contains least engine transients over the WLTC. The cumulative sum of pumping loss in Fig. 5 (d) implies improvement in fuel economy and hence the proposed NMPC achieves better tracking of set points and fuel economy simultaneously. The NMPC allows better tracking of torque at the peaks of torque increment than the production-line controller. This finding is analysed in more detail with the time series data presented in Fig 6. The lower tracking error of torque corresponds to better driveability of the vehicle, as well as effective satisfaction of (7k).

Fig 6 shows the time series from simulation (left) and HiL (right). The set points of each controller differ slightly since they operate at different conditions including temperature and BM EP. The NMPC shows more accurate tracking of oxygen concentration during transients (282-285, 1026-1032 s), whilst the production-line controller displays an undershooting trend (282.5, 1033 s). However, the NMPC displays a tracking offset of oxygen during a steadier period (293-302, 1043-1048 s). This offset is due to model-plant mismatch and can be reduced with a greater value of the integral gain. However, using greater integral gain degrades the overall tracking performance. The gain value may vary by the operating point of the engine but is not studied in this work. The NMPC also demonstrates better satisfaction of the lambda limit (Fig 6 (g)) than the production-line controller. Meanwhile, the NMPC allows the engine to meet the torque demands better than the production-line controller. Finally, the NMPC slightly reduces the pumping loss at peaks of the boost pressure (283, 1031, 1034 s) and also when the engine torque reduces (1037, 1043 s). This allows the engine to operate at higher efficiency and hence better fuel economy.

Fig 7 shows the compressor operating points for each duty part of the WLTC. The NMPC and production-line controller share a similar operating region without any choking or surging of the turbocharger. During heavier duties (H, EH parts of the WLTC), the NMPC operates the turbocharger closer to
Fig. 7. Operating points of the compressor for each duty part of the WLTC. NMPC controls the VNT to operate in similar area to that of the production-line controller. In H and EH duty parts, the NMPC operates the compressor with tighter distribution to the diagonal line that corresponds to higher compressor efficiency whilst fulfilling the tracking objectives.

Table IV shows the performance advantage of the NMPC on HiL implementation. The tracking advantage of the NMPC on HiL implementation is even higher than that for desktop simulation. In contrast, the production-line controller achieves better tracking of torque which reflects in the negative improvement in Table IV. In Fig 6 (a) (right half, 286, 1033, 1042 s), the production-line controller meets the rapidly increasing torque demands. Corresponding to the peaks of torque, the production-line controller records severe violations of the lambda limit in Fig 6 (g). The NMPC, in contrast, performs consistently from desktop simulation to HiL in respecting the lambda limit. The results from HiL differ slightly from that of desktop simulation because of an un-modelled communication latency between the host and A80Q7 board. This latency is caused by the asynchronous implementation of CAN read/write on the A80Q7 board. The latency results in a delay in the estimation of cylinder mass of charge and hence in fuel adjustment. However, comparing the results of Table IV with Table III shows that this latency has a minor impact on the tracking performance. Note that practical implementation of these controllers directly adopts analogue or digital IOs. It is therefore anticipated that the observed delay would not be present or would be significantly smaller.

The real-time performance and computational requirements of the proposed NMPC are evaluated using an ARM Cortex-A7 embedded processor running at 480 MHz, which has a comparable clocking rate to that of an ECU. Table V compares the execution time of the proposed NMPC against the production-line controller. Typical manufacturers sampling time to control the dynamics of the airpath of engines is 10 ms. The worst case execution time was 2.94 ms. This demonstrates the ability of the developed NMPC to be used on production ECUs.

Table V

<table>
<thead>
<tr>
<th>Included Airpath Controller</th>
<th>Production-Line Airpath Controller</th>
<th>NMPC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best Case (ms)</td>
<td>0.51</td>
<td>1.33</td>
</tr>
<tr>
<td>Worst Case (ms)</td>
<td>1.82</td>
<td>2.94</td>
</tr>
<tr>
<td>Median (ms)</td>
<td>0.66</td>
<td>1.74</td>
</tr>
<tr>
<td>Mode (ms)</td>
<td>0.65</td>
<td>1.73</td>
</tr>
<tr>
<td>Average (ms)</td>
<td>0.66</td>
<td>1.80</td>
</tr>
<tr>
<td>Standard Deviation (ms)</td>
<td>0.04</td>
<td>0.23</td>
</tr>
</tbody>
</table>

Compared to existing works, the developed NMPC achieves good real-time performance. Using hardware of identical clock rate, [19] reported a worst case of 10 ms and did not offer a comparison with respect to a production-line controller. Work in [18] approximates its computing time with a ratio of clock rate which yields a worst case execution time of 3.89 ms for a 480 MHz processor. Compared to [18], the developed NMPC additionally considers the LP EGR but does not incorporate a separate feed-forward design to compensate for fast change of dynamics. Finally, the developed NMPC considers more objectives including tracking and fuel economy at a competitive execution time than the NMPC in [20] that optimises a single objective of engine efficiency.

VI. CONCLUSIONS & FUTURE WORK

This work has presented a NMPC for the tracking control of the airpath for a EURO 6 CI engine. The NMPC tracks the set points of boost pressure and cylinder oxygen concentration using dual-loop EGR and VNT, at 10 ms rate. The work utilises prediction models of multi-rate based on the observed slow dynamics of boost pressure. The prediction of boost pressure takes 10 times longer step than the rest of the model. This formulation, along with the convex prediction models, reduces the computational footprint of the resulting control problem.

The developed NMPC is benchmarked against a production-line controller, using a simulation study and HiL. The approach of using the multi-rate prediction models is demonstrated to improve fuel economy, torque tracking, tracking of boost...
pressure and in-cylinder oxygen by 0.89%, 27%, 10% and 18%, respectively, against the production-line controller using a simulation study. Subsequent HiL implementation confirms the benefits and shows improvement of fuel economy, tracking of boost pressure and in-cylinder oxygen by 0.98%, 12% and 21%, respectively, at the cost of 7% degradation in torque tracking due to the un-modelled communication latency. The developed NMPC, along with the entire engine control software, records a worst-case execution time of 2.94 ms on a 480 MHz ARM Cortex-A7 processor.

The work presented in this paper demonstrates the applicability of proposed NMPC for potential production use. Despite the real-time property, the NMPC requires moderate development work as it uses one single set of data-driven models and achieves good tracking performance using one set of weighting values over the WLTC.

Future works include an on-vehicle experiment using a production ECU, and development of adaptive integral gains to further improve tracking performance.

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